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Completed Research Paper

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Abstract

Big data has managed in a very short time to dominate the interest of researchers and managers, vastly changing the way information is generated and used in decision making. Nevertheless, there has been disproportionate focus on the technical aspects of this emerging technology, and limited attention on other relevant organizational elements. Past research in IT business value has demonstrated that investments alone do not generate business value; rather, firms need to develop idiosyncratic and difficult to imitate capabilities. Drawing on the resource based view and dynamic capabilities view of the firm, this study examines the resources that are necessary to develop a big data analytics capability, identifies the organizational capabilities they enable, and determines factors that moderate or condition the value of a big data analytics capability. Employing a multiple case study approach on six international firms, we develop a deeper understanding of the importance of big data analytics resources and the mechanisms through which they leveraged towards the strengthening of organizational capabilities.

Keywords: Big Data Analytics, Resource-Based View, Dynamic Capabilities, Business Value

Introduction

Big data analytics and its application in driving organizational decision making has attracted much attention over the past few years. An increasing number of firms are investing in big data analytics with the aim of deriving important insight which can potentially provide them with a competitive edge (Constantiou & Kallinikos, 2015). The need to harness the potential of rapidly expanding data volume, velocity, and variety, has seen a significant evolution of techniques and technologies for data storage, analysis, and visualization. Nevertheless, there is limited understanding of how organizations need to change to embrace these technological innovations, and the business shifts they entail (McAfee et al., 2012). Despite the hype surrounding big data, the previously mentioned predicaments still remain largely unexplored (McAfee et al., 2012), severely hampering the business and strategic potential of big data. Most efforts to date have been primarily focused on infrastructure, intelligence, and analytics tools; substantially disregarding other related resources, as well as how these socio-technological developments should be incorporated into strategy and operations thinking.

While there have been several research commentaries stressing the importance of delving into the whole spectrum of aspects that surround big data analytics (Constantiou & Kallinikos, 2015; Markus, 2015), exploratory empirical literature on the topic still remains at an inaugurating state (Gupta & George, 2016; Wamba et al., 2017). Past literature reviews on the broader IS domain have demonstrated that there are multiple aspects that should be considered when examining the business potential of IT investments (Schryen, 2013). In addition, the specificities of each technological development need to be taken into account in order to fully capture the interdependencies that develop between them and how they produce value at a firm level. Literature on IT business value has predominantly used the notion of IT capabilities to refer to the broader context of technology within firms, and the overall proficiency in leveraging and mobilizing the different resources and capabilities. It is therefore important to explore the domain specific aspects that are relevant to big data analytics within the business context (Kamioka & Tapanainen, 2014).

The lack of empirical work in this direction significantly hinders research concerning the value of big data analytics, and leaves practitioners in unchartered territories when faced with implementing such initiatives in their firms. Thus, the aim of this paper is to explore the resources that are important when investigating big data analytics and how they relate to successful adoption. To do so, we built on a multiple case study approach using data from six firms in Europe. We develop a theoretically guided research framework which helps us determine thematic areas to be investigated in the case studies and test the importance of each concept as well as the overall business value of firms' big data analytics capabilities. Our results uncover some critical aspects that emerged in the analysis of our data and can serve for the basis of future research. The rest of the paper is structured as follows. In the next section we describe the two main theories used to develop our research framework, and summarize existing work on the business value of big data analytics. Then, we proceed to outline the research methodology employed, present the data collection methods and our sample, as well as define the main thematic areas we focus on. Finally, we present the results of our study, followed by a discussion and suggestions for future research.

Theoretical background

While there is a rapidly expanding literature on the business potential of big data analytics, there is limited work empirically grounded on established theories used in the IT-business value domain (Gupta & George, 2016). In order to derive meaningful theoretical and practical implications, as well as to understand prominent areas of future research, it is important to place the present study into a research framework and understand how the core artefacts are shaped and how they lead to business value (Constantiou & Kallinikos, 2015). As such, we employ a deductive approach grounded on the established resource-based view (RBV) of the firm, as well as the emerging dynamic capabilities view (DCV). The rationale for selecting these theoretical groundings is since the former provides a solid foundation upon which all relevant resources can be identified and evaluated towards their importance, while the latter enables the examination of the organizational capabilities towards which these resources should be directed in order to achieve competitive performance gains (Mikalef et al., 2016). Thus, the DCV complements the RBV by providing an explanation of the rent-yielding properties of organizational capabilities that can be strengthened or enabled by means of big data analytics (Makadok, 2001).

Resource Based View

The resource based view has been widely acknowledged as one of the most prominent and used theories in explaining how firms achieve and sustain a competitive advantage as a result of the resources they own or have under their control (Barney, 2001). According to rationale put forth in the RBV, an organization is perceived as a bundle of valuable tangible and intangible resources, which can be combined to generate a competitive advantage (Peteraf, 1993). The original RBV defines resources as rare, inimitable, and non-substitutable firm-specific assets that enable a firm to implement a value-creating strategy to generate rents (Barney, 1991). The notion of resources was further split to encompass resource-picking and capability-building, two distinct facets central to the RBV. Amit and Schoemaker (1993) define resources as tradable and non-specific firm assets, and capabilities as non-tradable firm-specific abilities to integrate, deploy, and utilize other resources within the firm. Thus, resources are used as the input of the production process while a capability is the proficiency to deploy these resources with the aim of improving productivity. In terms of types of resources, the literature on strategic management has predominantly employed the distinction of tangible, intangible, and human skills and knowledge (Wang et al., 2012). The RBV has been used extensively in the IT context through the notion of IT capabilities (Bharadwaj, 2000). IT literature recognizes that a competence in leveraging IT-based resources in combination with other organizational resources is a source of competitive and advantage (Pavlou & El Sawy, 2006). Past empirical studies have used the notion of IT capabilities to examine its direct (Bhat & Grover, 2005) or indirect impact on performance outcomes (Wang et al., 2012). The main premise adopted in these studies is that in order to develop a robust IT capability it is necessary for a firm to have invested in all the necessary resources (Wade & Hulland, 2004). Failure to invest in one type of resource may cause the collapse of the value of the rest, making it necessary to place equal importance to each (Mikalef et al. 2014).

Dynamic Capabilities View

The dynamic capabilities view of the firm has emerged as one of the most important theoretical perspectives in the study of strategic management and technology over the past decade (Schilke, 2014). Extending the resource based view of the firm, the dynamic capabilities view attempts to explain how a firm maintains a competitive advantage in changing environments (Eisenhardt & Martin, 2000). Therefore, the emphasis is shifted from internally within the company to the external environment and the necessary actions required in order to reconfigure existing means of operations to address constantly shifting demands. This shift has been sparked by commentaries from many researchers that the RBV does not adequately explain why certain firms attain a competitive advantage in situations of rapid and unpredictable change (Eisenhardt & Martin, 2000). During the past decade there have been considerable efforts in defining and framing the boundaries and conditions that characterize dynamic capabilities, yet, there are significant divergences. Based on the notion that firms must be able to be stable enough to continue to deliver value in their own distinctive way, and agile and adaptive enough to restructure their value proposition when circumstances demand it, there is a well-documented distinction between ordinary (operational) and dynamic capabilities (Drnevich & Kriauciunas, 2011). Ordinary capabilities enable a firm to make a living in the present, while dynamic capabilities act as a mechanism of evolution to changing requirements (Winter, 2003). However, the resources owned or controlled by the firm are imperative in determining what types of capabilities a firm can develop, and of what value they will be. In the context of IS literature, several studies have examined how IT infused in organizational capabilities can help firms renew or reconfigure their existing mode of operating (Pavlou & El Sawy, 2006; Mikalef et al., 2016; Mikalef & Pateli, 2017). Thus, what is important is to infuse IT investments into the organizational fabric in order to derive sustained competitive value (Kohli & Grover, 2008).

Big Data Analytics and Business Value

In the context of big data, it is important to identify the different types of resources, since the level of their infusion in various business functions can be a source of competitive differentiation (Davenport, 2006). When these resources and their related activity systems have complementarities, they are more prone to lead to a competitive advantage (Eisenhardt & Martin, 2000). To date there have been several studies that attempt to define the buildings blocks of firms’ big data analytics capability, that is the resources that are necessary to build upon (McAfee et al., 2012; Kamioka & Tapanainen,2014; Gupta & George, 2016; Mikalef eta l., 2016 Wamba et el., 2017). Yet, the majority of these studies adopt their conceptualizations from previous IT literature, with little regard towards the particularities of the big data context. It is argued that in order to understand the emerging big data paradigm and flesh out the business value it can deliver, it is important to comprehend the full spectrum of factors that are relevant (McAfee et al., 2012). Most research is rather fragmented which makes it difficult to evaluate the business value. For instance, Kaisler and colleagues (2013) identify data storage and data transport as important aspects pertaining to the value of big data. On the other hand, Seddon and Currie (2016) focus on aspects related to the characteristics of data itself, while Davenport and Patil (2012) place the spotlight on the human aspect of big data, and specifically on the importance of the data scientist. These are undoubtedly important elements, however, it is important for organizations to focus on the full range of resources which are needed to build a difficult to replicate big data analytics capability, and understand through what mechanisms and under what conditions it can deliver business value (Gupta & George, 2016). We therefore seek to integrate these theoretical perspectives, and combined with existing literature on big data analytics explore their importance in driving organizational capabilities.

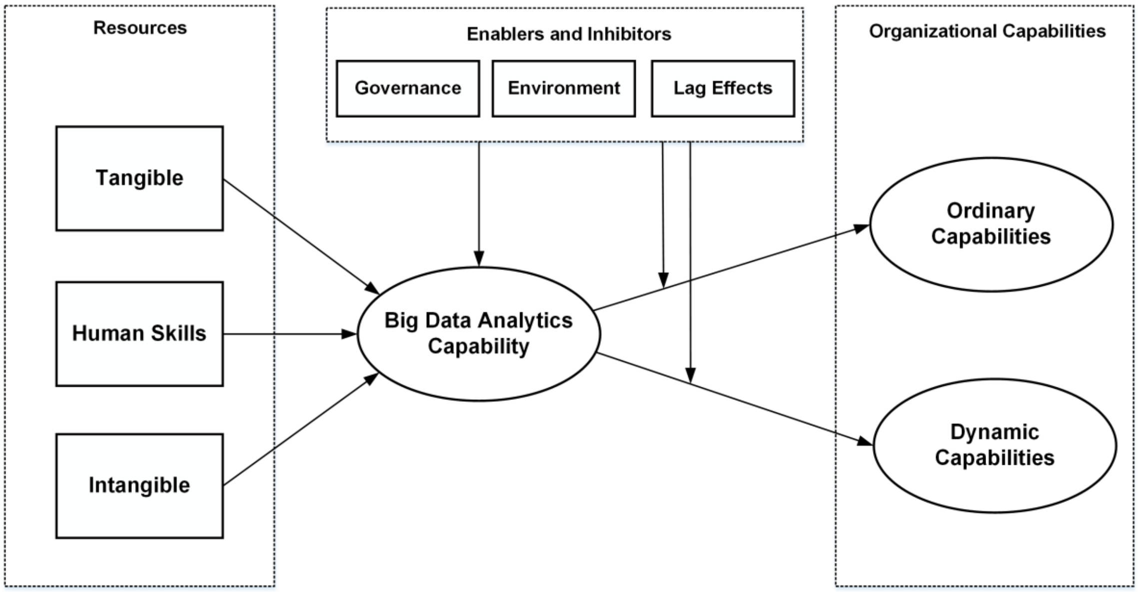

Figure 1 Research Framework

Methodology

Design

Starting from the theoretical background and the overview of existing literature on the business value of big data analytics, the present work aims to investigate the core resources and capabilities that are relevant in big data analytics projects and how they are associated. In particular, we have formulated the following research question to help guide our investigation:

What resources and capabilities should firms pay attention to during the implementation of big data analytics projects? What are the main enablers and inhibitors in the realization of business value?

We started by conducting a literature review with a focus on the building blocks of a big data analytics capability and on the possible catalysts and hindrances in attaining business value from such investments. The purpose of the literature review was to identify the main concepts that underlie the dimensions of the theories used within the context of big data. Then, we tried to understand the importance of these concepts through firms that have initiated big data projects. The research design followed is a multiple case study. We chose this approach as we wanted to observe the phenomenon of how a big data analytics capability is developed in a real business setting, as well as the difficulties faced when trying to utilize these capabilities in order to realize business value. Using multiple case studies allows us to identify both the technical aspects related to implementation, as well as the interaction with the business side of the company. Through multiple case studies it is also possible to enable a replication logic in which the cases are treated as a series of experiments that confirm or negate emerging conceptual insights (Battistella et al., 2017). We chose a deductive multiple case study analysis based primarily on interviews with key informants, and secondary on other company-related documents. This selection was grounded on the need to sensitize concepts, and uncover other dimensions that were not so significant in IT-business value studies (Gregor, 2006).

Research Setting

For the sample of our multiple case study we selected among firms that demonstrated somewhat experience with big data analytics, whether they had recently started or had invested considerable time and effort in this direction. In addition, we focused on medium to large size companies since the complexity of the projects they were involved in would give us a better understanding of the spectrum of requirements in big data initiatives. Lastly, the chosen firms operated in competitive and highly dynamic markets which necessitated the adoption of big data as a means to remain competitive. Therefore, efforts in developing strong organizational capabilities via means of big data analytics were accelerated. We selected different companies in terms of type of industry within the given boundaries, with the aim of doing an in-depth analysis and to be able to compare and contrast possible differences (table 1). The selected firms are considered established in their market with over 10 years of operations in the region of Europe.

Firm	Business areas	Established	Employees	Primary objective of adoption	Key respondent (Years in firm)
A	Consulting Services	1864	15.000	Risk management	Big Data and Analytics Strategist (4)
B	Oil & Gas	1875	16.000	Operational efficiency, Decision making	Chief Information Officer (6)
C	Media	1839	7.700	Market intelligence	Chief Information Officer (3)
D	Media	1889	380	Market intelligence	IT Manager (5)
E	Media	1996	170	Market intelligence	Head of Big Data (4)
F	Consulting Services	1996	5.500	New service development, Decision making	Chief Information Officer (7)

Table 1 Profiles of the studied firms

Data Collection

Interviews are a highly efficient way to gather rich, empirical data, yet, there is a limitation of information being subjective since it originates from respondents within the firm. This limitation can be mitigated by employing approaches that limit such bias. In this study we collected data from primary and secondary data sources for each firm. The primary source of data was direct interviews with chief information officers in which their attitudes, beliefs, and opinions were asked regarding their experience with big data initiatives their firm had undertaken. In order to avoid biased responses, data were collected through semi-structured interviews with managers that were directly involved in the big data initiative. Interviews were performed face-to-face in a conversational style, opening with a discussion on the nature of the business and then proceeding on to the themes of the interview guideline. When necessary, questions were clarified to encourage more accurate responses. Discussions were recorded and later transcribed for analysis. To corroborate statements of the interviewees, published information about the firms in the form of annuals reports, website information, as well as third-party online articles were used. Overall a semi-structured case study protocol was followed in investigating cases and collecting data (Yin, 2013). Three of the co-authors completed the independent coding of the transcripts in accordance with the defined themes as identified in Table 2 and Table 3. Each coder read the transcripts independently to find specific factors related to the required resources of a big data analytics capability, as well as on business value derived from such investments. This process was repeated until inter-rater reliability of the three coders (matched in pairs) was greater than 90 percent (Boudreau et al., 2001).

Data Analysis

The empirical analysis was performed by an iterative process of reading, coding, and interpreting the transcribed interviews and observation notes of the six case studies (Myers & Newman, 2007). At a first stage we identified and isolated a large number of concepts on the basis on the theoretical underpinnings that were discussed in the theoretical background section. For each case the standardization method was used to quantify these characteristics using an open coding scheme (Yin, 2013). This allowed us to cluster primary data in a tabular structure, and through the iterative process identify the relative concepts and notions that were applicable for each case. Collectively, these resources (Table 2) comprise what is referred to in literature as a big data analytics capability (Akter et al., 2016). In effect, the underlying logic suggests that firms that are able to manage these resources will present a firm-wide capacity of utilizing and leveraging big data technologies towards the strengthening of other organizational capabilities (Garmaki et al., 2016; Mikalef et al., 2016). The effect of a firms' big data analytics capability on performance is therefore considered as indirect, since it is mediated by other organizational capabilities (Akter et al., 2016; Mikalef et al., 2016).

Resources	**References**
Tangible	
- *Technology:* New forms of technologies are necessary for handling the large volume, diversity, and speed of data accumulated by firms. Further, firms employ novel approaches for extraction, transformation, and analysis of data.	Kamioka & Tapanainen, 2014; Gupta & George, 2016
- *Data:* Contemporary organizations involved in big data projects tend to capture data from multiple sources, independently of structures and on a continuous basis. Aspects concerning data such as quality, sources, methods for curating are important in deriving business value.	Kwon et al., 2014; Erevelles et al., 2016; Janssen et al., 2017
- *Financial:* Financial resources can be considered as direct investments in the support of these technologies, or working hours allocated to experimentation with utilizing the potential of big data.	Gupta & George, 2016; Wamba et al., 2017
Human Skills	
- *Technical Skills:* Technical skills refer to the know-how that is necessary to leverage the new forms of technology and to analyze the varied types of data to extract intelligence from big data.	Kamioka & Tapanainen, 2014; Gupta & George, 2016
- *Managerial Skills:* Managerial skills pertain to competencies of employees to understand and interpret results extracted from big data analytics and utilize them in meaningful ways.	Gupta & George, 2016; Braganza et al., 2017
Intangible	
- *Organizational Learning:* Organizational learning concerns the degree to which employees are open to extending their knowledge in the face of new emerging technologies.	Espinosa & Amour, 2016;
- *Data-driven Culture:* A data-driven culture describes the degree to which top management is committed to big data analytics, and the extent to which it makes decisions derived from intelligence.	Kamioka & Tapanainen, 2014; Gupta & George, 2016

Table 2 Thematic support for key resources

Apart from the key resources of big data analytics projects, this study includes the organizational capabilities that are enabled as part of their deployment as well as possible enabling or hindering elements. We establish a set of capabilities by focusing on the distinction between operational and dynamic ones as documented in the theoretical background section. As for potential enablers and inhibitors of the value of big data analytics capabilities we reviewed literature on IT-business value which builds on the resource based view and the dynamic capabilities view of the firm (Melville et al., 2004; Schryen, 2013; Mikalef & Pateli, 2016).

Concepts	**References**
Organizational Capabilities	
- *Ordinary:* Ordinary capabilities are those capabilities that enable a firm to make a living in the present by increasing revenue and reducing costs associated with the provision of products or services.	Drnevich & Kriauciunas, 2011

- *Dynamic:* Dynamic capabilities are those capabilities that are used to extend, modify, change, and/or create new ordinary capabilities.	Pavlou & El Sawy, 2006; 2011; Mikalef & Pateli, 2017
Enablers/Hindrances	
- *Governance:* The importance of governance of IT has been documented in past empirical literature with decisions about appropriation rights significantly affecting the value of IT resources.	Tiwana & Konsynski, 2010; Tallon, 2013
- *Lag effects:* There is substantial empirical evidence that the impact of IT investments needs to be considered under the prism of time lags.	Schryen, 2013
- *Environment:* The competitiveness, dynamism, and rate of technological change of the environment may have a substantial effect on the value IT delivers.	Schryen, 2013

Table 3 Thematic support for organizational capabilities and enablers/inhibitors

Results

After applying the previously mentioned method on the collected data, we visualized the outcomes in the form of a matrix. In Table 4 the importance of each resource is noted, as well as factors that enabled or hindered the potential value of big data investments towards their enablement of the different types of organizational capabilities. For the resources, black circles (●) indicate that the concept at hand was mentioned as being important and implemented in the big data strategy, whereas a blank circle (○) indicates that it had not been implemented up to the time of the interview. For enablers and hindrances, the presence of a black circle suggests that they were important aspects in realizing business value from big data investments. Finally, with regard to organizational capabilities, the presence of a black circle indicates that the firm has managed to utilize its big data investments towards the strengthening of ordinary and/or dynamic capabilities.

Tangible Resources

In terms of tangible resources, all six cases indicated the importance of technology in their big data initiatives. Considerable investments had been made on technologies such as Hadoop, NoSQL, H-Base, MongoDB, and Cassandra. For storing data some firms (E and F) also made use of Amazon Web Services and Microsoft Azure. It was frequently mentioned by respondents that finding the right technologies was not a major concern, and that there are several alternatives to fit each case. Scalability and connectivity of technologies was cited as being important since the data accumulated and processed fluctuates considerably. In addition, the general consensus was that although technological resources are fundamental for initiating a big data project, they are unable to provide a competitive advantage *per se*. Nevertheless, respondents of firm A, B and F noted that they were placing considerable effort in technologies to collect data via sensors and other means, and being able to analyze data captured from these instruments in real time.

Concerning data, there was a lot of discussion by the respondents on finding high quality data which can be used to accurately make decisions. In many cases respondents indicated that they used multiple sources of data in order to fulfil their business objectives and ensure quality, as was mentioned for instance in firm A:

> ¨*We fill in some of our own data, some open data, some bought data, some customer data, and some aggregated data [...] we buy access to numerous datasets worldwide and have some data we have collected for years*¨

The outsourcing of data was also mentioned by interviewees in firms C, E and F. This finding is particularly important since past literature in the domain of big data rarely mentions the need to purchase data from external sources to complement analytics. Furthermore, a strong emphasis was placed by interviews on the process of cleansing data and the quality of the final datasets that will be used for analysis. In firm A there was mention of a need to establish a framework to be able to assess and improve the quality of data from any available sources. In firm D, there was mention of the importance of historical data since it helps show trends. Fragmentation was also noted as being a problem according to the respondent in firm B:

> *¨Biggest challenge is access to data. Data is very fragmented. Available in lots of places but the routines to access it are rather old [...] our biggest problem is finding data¨*

Financial resources were seen as very important in most of the firms, since in the transition period from experimenting with big data to actually utilizing analytics to make decisions considerable investments must be made, both for infrastructure as well as for working hours that could be spent elsewhere.

Human Skills

Technical skills were credited as being one of the most important, and difficult to acquire, resources for all firms participating in this study. As the respondent for firm F said:

> *¨Lack of competencies has to be the most major challenge we face. In the market there are not people with experience. There is a gap in the skill that is quite remarkable at the moment, and the gap is increasing because there is a lot of new demand for new skills¨*

When examining the technical skills required, three primary categories were identified. The first were big data architects who develop a blueprint of the data sources as well as appropriate technologies to harness their potential. The second was personnel with technical big data competencies (big data engineers) able to manage data acquisition, storing, cleansing, and coding. The third concerned employees with the right mathematical and statistical competencies to make predictive and analytical models and visualize results, while also being proficient in communication skills. For the latter category, several interviewees stated that they must have the ability to see possible combinations of data to get new results. It is quite common however in firms that are in an early stage of big data to assign all three roles to the same person (According to the experiences of respondents from C and F). In some cases, respondents stated that they even enter alliances or strategic partnerships in order to acquire people that possess such skills (Firms A and B).

On the other hand, managerial skills in big data projects were seldom mentioned. This can be attributed to the fact that most initiatives start out as technology experimentations from the technical division of firms, with little input towards what type of analytics would be required from the management. From the results obtained from firm D it is claimed that managerial skills are usually developed after the experimentation with big data and the understanding of their possible potential. The respondent in firm F stated that in unit divisions, younger managers were more prone on driving big data projects than older ones since they are also more open to new technologies.

Intangible Resources

Due to the fast rate of change of technologies, tools, and programming languages used to support big data projects, one of the most cited factors in being successful according to respondents was the capacity to continuously learn new things. Firms use multiple ways to constantly learn new things about big data, such as survey leaders, meet with market professionals, and read scientific papers (Firm A and C). Due to the lack of technical skills, some respondents also noted that they had to train themselves in these new technologies. For instance, the respondent for firm B states:

> *¨We've done it our self. Thus, own education. Hadoop expertise was very difficult to obtain so we had to actually train people within the company¨*

This need for continuous learning is also noted by the respondent in firm F, who argues that it is necessary for employees to be flexible and spend some of their time acquiring new emerging skills:

> *¨Often business and information technology architecture changes, and IT staff exits into new roles so it is important they gain new knowledge and skills fast¨*

Equally as important as an inclination to learn new skills, is the culture towards data-driven decision making according to interview findings. A critical part for the success of a big data project is the support received from top management. Respondents indicated that although top management was rather sceptical about investing in big data initially, recent positive outcomes as well as the emerging trend have been able to shift opinions. Yet, there is still some scepticism towards the validity of results obtained from analysing big data which is apparent from the respondent in firm A and B respectively:

> *¨Big data makes it possible to bring out a basis for decision making that you previously could not access. The belief that the analysis result is objective, makes you more confident in taking*

> *decisions [...] however, there are cases when the analysis has provided wrong information, so you should still have a healthy scepticism towards the result of the analysis.* ¨

> ¨*In the wake of the big data enthusiasm, there has slowly but surely been a path of transformation to organizations and a deeper dependence*¨

In the case of the media companies top management support and the transition to a data-driven culture has been even more apparent. This is reflected from the respondent of firm C.

> ¨*Management sees this (big data) as essential to success of the industry we are in. From corporate management there is a strong buy-in regarding big data*¨

In sum, it can be said that the data-driven culture has to do with the competitive pressures of the environment, the digitization of the business and availability of data, as well as on the openness of top management to embrace data-driven decision making.

Enablers/Hindrances

Considerable discussion concerned the issue of governance in big data projects, especially with regard to the governance of data. While IT governance is rather well established from past initiatives, it seems that the emergence of big data sets opens a new frontier for managers. This is particularly evident in the quotation of respondent from firm F:

> ¨*It is a big issue to establish a governance plan for big data, if you don't, then there will be no guarantee that data are of the expected quality. In addition, acquiring, storing, managing, and processing big data will be done in an ad hoc manner which is not very efficient*¨

Similar comments from the other respondents indicate that it is imperative for firms to establish concrete data management plans that span the whole lifecycle of big data and take into account the technologies and people that will be involved.

A commonly mentioned theme in the interviews was the amount of time it took to see business value in big data initiatives. For one, in most cases there was a period of experimentation in which the primary objective was to get accustomed with big data technologies and how different datasets could be utilized, as well as identifying gaps in knowledge and expertise. From the feedback provided by the respondents it is suggested that, typically, big data projects take 3-5 months to results in any identifiable business value. In certain cases, this period may even extend to close to one year. Nevertheless, it is cited that even after such a period it is difficult to isolate exactly the value delivered from big data and quantify it in a measurable way. It is even suggested that the competitive advantage gained from big data might be impossible to identify, since it is perceived as a means to stay in the game and attain a competitive par, as stated by firm A's respondent:

> ¨*Big data is an investment that we do regardless of whether it pays off in isolation [...] it is a necessary approach to be in business in 10 years.* ¨

As was previously mentioned, the uncertainty of the environment as well as competitor decisions to embrace big data, are significant factors in the decision of firms to initiate big data projects. In addition, the competitive environment is also noted to condition the value derived, with those firms that are first to start big data being more likely to gain a competitive edge. This is especially evident for firms that have customers with low switching costs, such as those in the media industry. As put by respondent in firm C:

> ¨*It is absolutely necessary for our survival, to put it simply. We must do the same, if not we slowly become uncompetitive* ¨

Organizational Capabilities

For all cases there was conclusive proof that big data had influenced organizational capabilities in one way or another. In most cases big data helped improve operationally efficiency and accuracy of choices. Primarily, big data projects were used to improve existing means of operation, by reducing costs, identifying areas in which services and products can be enhanced, and more precisely identifying customer segments and delivering tailored made solutions. Furthermore, it was particularly noted that media companies focused a large proportion of their efforts on user generated data, and performed sentiment analyses to identify areas in which they could improve their experience. As such, they drastically improved ordinary capabilities. Adding to the above, in some circumstances big data gave insights to top managers to totally revamp their prevailing product and service offerings. For instance, firm F based its pricing and service offerings based on the analysis of big data, while firm C combined data from multiple sources to generate a new service that alerts users based on their combined preferences on products they may be interested in that are on sale from local sellers. Consequently, big data through the appropriate mechanisms can be regarded as enablers of dynamic capabilities.

	A	B	C	D	E	F
Resources						
Tangible						
- Technology	●	●	●	●	●	●
- Data	●	●	●	●	●	●
- Financial	●	○	●		●	●
Human Skills						
- Technical Skills	●	●	●	●	●	●
- Managerial Skills		○		●		
Intangible						
- Organizational Learning	●	●	●	●	●	●
- Data-driven Culture		○	●	●	●	●
Note: ●, Implemented; ○ Not implemented						
Enablers/Hindrances						
- Governance	●		●	●	●	●
- Lag Effects		●	●			●
- Environment			●	●	●	●
Note: ●, Important factor						
Organizational Capabilities						
- Ordinary	●	●	●	●	●	●
- Dynamic			●			●
Note: ●, Improved						

Table 4 Resources, enablers, and hindrances on organizational capability outcomes

Additional Findings

While our initial thematic analysis focused on a large number of resources and other relative factors in realizing business value out of big data analytics investments, there were some aspects that emerged during the interviews that were not originally included. Perhaps the most prominent one was that many respondents indicated that there is a frequent occurrence of resistance to change in the face of big data. Strikingly, this resistance can be manifested either by top executives that are unaware of the potential benefits, or by employees of the IT division that are faced with new skills and tools that they must learn to use. In terms of these two, the respondent of company B mentions the following for the former and latter phenomena:

> ¨*There was a period where there was reluctance on the highest level. They saw big data as just a cost. Now it is the middle management level that is reluctant to changes.* ¨

> ¨*A good part of this is related to the change of the business. Often the problem is that people are not always so interested in change. People are afraid of losing their jobs.* ¨

Discussion and Conclusion

This study investigated the core resources required by firms to develop a big data analytics capability. In addition, we sought to examine what impact it had on the enablement of two distinct types of organizational capabilities, ordinary and dynamic, as well as possible enablers and hindrances that could condition any possible business value. We add to existing literature in four main areas. First, we presented a theoretically guided framework to examine core resources associated with big data and their potential business value. Second, we provide a deeper understanding of the issues associated with the core resources that IT managers are faced with handling. Third, we present several enabling and inhibiting factors that affect the derived value that have scarcely been mentioned in big data literature. Fourth, we examine the different forms in which business value from big data analytics can be realized by distinguishing between their impact on ordinary and dynamic capabilities.

From a theoretical point of view, our study contributes to the emerging literature of capturing the business value of big data analytics investments (Kamioka & Tapanainen, 2014; Gupta & George, 2016; Mikalef et al., 2016; Wamba et al., 2017). While early literature focused on big data analytics capability as a technical capability, our findings demonstrate that managerial, social, and relational aspects are important aspects. In addition, our findings uncovered practices that are hardly documented in literature, such as buying data-sets from third parties or the tendency of firms to form alliances and partnerships in order to gain much needed technical and analytical skills. These are important factors to consider when implementing big data projects. In addition, the fact that pilot projects are necessary before the actual deployment of real business cases, or that the presence of inertia manifests itself at multiple levels in the firm are critical components in driving successful big data initiatives (Besson & Rowe, 2012). Hence, our study contributes to a broader understanding of the components that comprise a big data analytics capability. Adding to these, we identify conditions that coerce firms to start investing in big data, such as competitive pressures, as well lag effects which may delay the realization of business value. Finally, we demonstrate that big data analytics can result in the enhancement of ordinary and dynamic capabilities, and therefore can be valuable to the existing operation of businesses while also contributing to new directions.

In terms of practical implications, our study unveils to managers the process and core-resources they should focus on when planning to delve into a big data analytics project (van de Wetering et al., 2017). It provides insight not only on the main issues they must take into account, but also on the possible options they have or the decisions they can make to overcome potential hurdles. In addition, the challenges faced by the sample of the six firms, can guide future ventures in formulating governance policies and deployment schemes to overcome potential obstacles. While this study presents some novel contributions, it does include certain limitations which future research can seek to address. The causal relationships between the variables as described by our framework would be best suited to be examined through a large-scale quantitative study. While uncovering them through multiple-case studies is a starting point, it by can no means be confirmed through a qualitative analysis on such a sample. In addition, a large-scale quantitative analysis could provide more granularity towards the conditions and limits to which big data analytics add value, and shed some light on contextual factors that are of importance, particularly using a complexity theory approach (Mikalef et al., 2015).

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